Government of Andhra Pradesh Commissionerate of Collegiate Education

Academic & Administrative Audit of Degree Colleges (2024-25)

Format - III A (To be Filled by Faculty and handed over to Academic Advisor)

Zone: II	District:KRISHNA
Name of the College and Address	Govt. Degree College,Avanigadda
Name of the Lecturer	N.Swarna Jyothi
Name of the Subject	Computer Science
Date of Joining in Degree	22-08-2022
	Date of Retirement 01-09- 2047

S.No	Key Indicator	List of files/ documents to be kept ready as a proof of Key Indicator	Information in support of the key indicator	Key Aspect Scores	Predetermined Weightage (Wi) for Key Indicator	Key Indicator Grade Points (KIGP) (A =3; B=2; C=1; D=0)	Key Indicator Wise Weighted Grade Points (KIWWGP) = KIGP X Wi	KIWWGP as per Acdemic Advisor's grading	Guidelines
I-CURRICULAR ASPECTS									
1	Curricular Planing and Implementation (for Autonomous Colleges - Efforts for Curriculum Desing and Development to be considered)	Preperation and Implementaion of 1. Annual Academic Curriculum Plan 2.Course Objectives & Outcomes	Course wise/Sem wise Records for the Academic Year	2x5= 10	30	A	90		1)All five key indicators =3 Grade points/A 2)Any four key indicators =2 Grade points/B 3)Any two key indicators =1 Grade points/C 4)No Indicator=0/D
		3. Teaching Diary 4. Lesson Plans	Course wise/Sem wise Records for the Academic Year	2x5= 10					
		5. Active Participation in BOS	Invitaion Letter & Attendance	10					
2	Curriculum Flexibility/Enrichment	1. Additional inputs related to Curriculum of the courses taught	a)Course wise/Sem wise additional inputs Reports	10	20	A	60		1)All three key indicators =3 Grade points/A 2)Any two key indicators =2 Grade points/B 3)Any one key indicator =1 Grade point/C 4)No Indicator=0/D
		2.Value added courses offered & completed a)Certificate b)Diploma c)Any Online courses like MOOCs	b)Report on Certificate/ Diploma c)Any Online courses like MOOCs	2x5=10					
3	Feedback system	Feedback on Curriculum by Students a) Collected b) Analyzed c) Action taken	Course wise/Sem wise a)Reports of Feedback b)Analysis Reports c)Action taken Report	10	10	A	30		1)All three key indicators =3 Grade points/A 2)Any two key indicators =2 Grade points/B 3)Any one key indicator =1 Grade point/C 4)No Indicator=0/D
II-TEACHING, LEARNING & EVALUATION									
4	Catering to Student Diversity	1. Report on grouping of students into Slow, Moderate and Advanced learners 2. Course wise activities designed for Slow, Moderate and Advanced learners	1.Course wise/Sem wise Reports with lists of students (Slow, Moderate and Advanced learners) 2.Course wise/Sem wise Activities designed for Slow, Moderate and	10	20	A	60		1)All three key indicators =3 Grade points/A 2)Any two key indicators =2 Grade points/B 3)Any one key indicator =1 Grade point/C 4)No Indicator=0/D
		1. Report on Course wise Bridge Courses conducted 2. Report on Course wise Remedial coaching conducted	1.Course wise/Sem wise Reports on Bridge Courses conducted 2.Course wise/Sem wise Report on Remedial coaching conducted	2x5=10					
5	Teaching-Learning Process	1. Report on student centered methods implemented (Course wise) 2.Report on implementation of ICT in teaching and learning (Course wise) or Report on implementation of Computer/Internet assisted learning (Course wise) 3. Report on the Use of LMS tools (Course wise) 4. Contribution for the development of LMS in the concerned subject 5. Report on innovative pedagogical Tools used	Course wise/ Sem wise Reports	50	50	A	150		1)All five key indicators =3 Grade points/A 2)Any three key indicators =2 Grade points/B 3)Any two key indicator =1 Grade point/C 4) Below two=0/D

6	Teacher Profile and Quality	1. Report on Seminars/Conferences/ Workshops/ Guest Lectures organized 2. Report on Participation in Seminars/Conferences/Workshops/ Guest Lectures/ Invited talks 3. Awards and recognition 4. Participation in Short term/ Orientation /Refresher courses/FDPs 5. 1 - Content Development /MOOCs (Massive Open Online Courses)	Reports and Certificates	30	30	B	60		1)Any five key indicators =3 Grade points/A 2)Any three key indicators =2 Grade points/B 3)Any two key indicator =1 Grade point/C 4) Below two=0/D
7	Evaluation Process and Reforms	1. Report on Formative Evaluation (CIE) 2. Assignments-Critical, Innovative, text book and Internet based 3. Involvement in Summative evaluation 4. Maintaining Marks Register & Result Analysis register	Department wise reports regarding 1. Mid exams, Seminar Reports, Assignment books, Projects and any other tools of Internal Assessment 2. Departmental Internal Marks Register for CIA	10 10 5 5	30	A	90		1)All four key indicator Metrics =3 Grade points/A 2) Metrics 1, 2, 4 =2 Grade points/B 3)Metrics 1, 2,3 =1 Grade point/C 4) Below two=0/D
8	Student Performance and Learning Outcomes	1. Announcement and Attainment of Course Outcomes 2. Report on Student seminars/ Student demonstrations (Course wise) 3. Report on activities like Quiz/ Group discussion/ Poster presentaion (Course wise) 4. Report on Field trips (Course wise) 5. Report on Student Study projects (Course wise)	Course wise Reports	5x6=30	30	A	90		1)All five key indicators =3 Grade points/A 2)First KI Metric and any three other =2 Grade points/B 3)First KI Metric and any two other =1 Grade point/C 4) Below two=0/D
		III-RESEARCH, INNOVATIONS AND EXTENSION							
9	Funding obtained for Research (Govt./Non-Governmental Bodies)	1. Minor Research Projects 2. Major Research Projects 3. Consultancy Projects	Letter of intimation and award letters (For Current Year only Either Ongoing OR Completed)	5 10 5	20	D	0		1)All three key indicators =3 Grade points/A 2)Any two key indicators =2 Grade points/B 3)Any one key indicator =1 Grade point/C 4)No
10	Research Publications and Awards	1. Papers Published in Journals / Chapters published in edited volumes 2. Books published as single author 3. Books published as Co-Author 4. Papers/Chapters published as Co-Author (Note: A maximum of 3 publications in Scopus/Web of Science/ICI or UGC -CARE Listed journals/Any book with ISBN shall be considered) 5.Research Guideship 6.Awards in recognition		10 15 10 5 10 10	60	B	120		1)Any three key indicators =3 Grade points/A 2)Any two key indicators =2 Grade points/B 3)Any one key indicator =1 Grade point/C 4) No Indicator=0/D
11	**Extension Activities**	Academic Extension activities through DRC/ Faculty Outreach (Curriculum/ Skill/Domain related)	Reports in the NAAC format	10	20	A	60		1)All three key indicators =3 Grade points/A 2)Any two key indicators =2 Grade points/B 3)Any one key indicator =1 Grade point/C 4)No Indicator=0/D
		Involvement in activities related to community service a. Sensitising the students about the value of Community Service b. Organising the activity (A maximum of 5 Programmes resulting in Community Service like ODF/Swachh Bharat/UBA etc)	Reports in the NAAC format	5+5					
12	**Functional MoUs /Collaborations with Govt and Non Governmental Organisations**	1.Collaboration with University/ Industry/NGO/ Any other Agency 2. Consultancy offered 3. Amount generated through Consultancy.	MoUs - 5 points Consultancy offered -10 Amount generated through Consultancy - 5 points	20	20	B	40		1)All three key indicators =3 Grade points/A 2)Any two key indicators =2 Grade points/B 3)Any one key indicator =1 Grade point/C 4)No Indicator=0/D

		IV - USE OF INFRASTRUCTURE & LEARNING RESOURCES							
13	Physical facilities	Infrastructural facilities in the Department/Colleges a. Use of Digital Classrooms b. Use of Virtual Classroom c. Use of Labs d Use of Library e. Nlist usage f. Maintenance of Departmental Library	Log books related to usage	20	20	A	60		1)Any four key indicators =3 Grade points/A 2)Any three key indicators =2 Grade points/B 3)Any two key indicators =1 Grade point/C 4) Below two Indicators=0/D
		V- ROLE IN STUDENT SUPPORT AND PROGRESSION							
14	Student Support	1. Counseling of students as Mentor/ Class teacher a. Student Profile Collection b. Semester wise updation and maintenance. 2. Any other Study Material /Guidance a)Academic guidance for the advanced learner (offering suggestions/reference books) b)Handholding the slow learners (offering study material/ question banks) 3. Guiding/Monitoring Students for CSP/Internship 4. Organizing/Participation in Parent Teacher	Reports in the NAAC format	20 10 10 10	50	A	150		1)All Four key indicators =3 Grade points/A 2)Any Three key indicators =2 Grade points/B 3)Any Two key indicator =1 Grade point/C 4)Below two=0/D
15	Student Progression	Report on Programme/Course wise students' progression to a)Higher Education b)Employment c)Entrepreneurship	Reports in the NAAC format	10 10 10	30	B	60		1)All three key indicators =3 Grade points/A 2)Any two key indicators =2 Grade points/B 3)Any one key indicator =1 Grade point/C 4)No Indicator=0/D
		VI- ROLE IN INSTITUTIONAL GOVERNANCE							
16	Participation in Institutional Governance and Leadership	a)Contribution to Departmental Vision & Mission and Departmental Action Plan b)Participation in different institutional committees and preperation of committee reports c)Participation in different institutional activities that focus on value based education d)Contribution to IQAC/quality initiatives	Reports in the NAAC format	4x10	40	A	120		1)All Four key indicators =3 Grade points/A 2)Any Three key indicators =2 Grade points/B 3)Any Two key indicator =1 Grade point/C 4)Below two=0/D
		VII - BEST PRACTICES							
17	Best Practices	Identification and Contribution to a)The Departmental Best practices b)Institutional Best practices	Reports in the NAAC format	20	20	A	60		1)All Two key indicators =3 Grade points/A 2)Any one key indicator =2 Grade points/B 3)No Indicator=0/D
		Total Grade points			500		1210		

Name & Signature of the Principal

D-~ ~

N.S. Jhtt

PRINCIPAL
GOVT. DEGREE COLLEGE
AVANIGADDA, Krishna Dist.

Name & Signatures of the Academic advisors

1)
2)
3)

KRISHNAUNIVERSITY

MACHILIPATNAM

No. KRU/AAC/UG/BOS/Computer Science and Cognitive Systems/2024-25

Date: 30.11.2024

PROCEEDING OF THE VICE-CHANCELLOR (I/C)

Present:Prof.R.Srinivasa Rao

Sub:- KRU/AAC/ UG BOS Computer Science and Cognitive Systems syllabus for AY 2024-25-Orders Issued.

Ref:- Note orders of the Vice-Chancellor, Dt.29.11.2024,Computer No. 2589119, File No. SCHE-KRU/362/2024-KU-EHE73.

-oOo-

ORDER:

The Vice-Chancellor is pleased to issue orders for the UG Board of studies in Computer Science to hold a BOS meeting in the online mode to finalize the resolutions, syllabus, model question papers and any other related matters for B.Sc. Honors, in Computer Science and Cognitive Systems (Major) for I, II, III, IV, V, VI, VII and VIII semesters.

He has issued orders to entrust the members of the BOS in UG Computer Science as mentioned in proceedings No.KRU/AAC/Board of studies /Computer Science/2023, dated 20.12.2023, to frame the resolutions, syllabus, model question papers and any other related matters for B.Sc. Honors, in Computer Science and Cognitive Systems (Major) also, by holding a meeting in the online mode within a week, to be organized by the BOS chairperson by communicating and coordinating with the other members of BOS.

He has also authorized the director, Academic Audit Cell, Krishna University, to communicate this with the said BOS members. After the meeting is over, all the relevant documents affixed with signatures are to be submitted to the office of the academic audit cell,in both hard and soft forms, for further processing, along with the filled-in claim forms within ten days from the date of this proceeding.

The Vice-Chancellor has also permitted to pay sitting allowance only, through online/NEFT payment for all the members of the BOS, for attending online BOS meeting, from the "Affiliation Account" for the financial year 2024-25.

(BY ORDERS)

Sd/
REGISTRAR

Copy to:

N.S.Datta

1. PSto theVice-Chancellor
2. PAto theRegistrar
3. File

Signed by Sobhan Babu I
Date: 03-12-2024 17:25:5
Reason: Approved

SURYA
ENGINEERING COLLEGE
PASSIONATE ABOUT INNOVATION

International Conference on Multi-Agent Systems for Collaborative Intelligence

ICMSCI International Conference on Multi-Agent Systems for Collaborative Intelligence

Date: 20 – 22 January, 2025
Organised by
Surya Engineering College
Erode, Tamil Nadu, India

IEEE

Certificate of Participation and Presentation

This is to certify that

Nadakuditi Swarna Jyothi

has participated and presented a paper titled

Cuscuta Detection and Classification of Blackgram Plant Leaf Diseases using Deep-Transformation Algorithm

in the International Conference on Multi-Agent Systems for Collaborative Intelligence (ICMSCI 2025) held on 20th, 21st & 22nd January, 2025.

M. [signature]
Session Chair

K. [signature]
Conference Chair
Prof. K. Senthilnathan

S. [signature]
Principal
Dr. S. Manoharan

N.S.Jyothi.

As per UGC guidelines an electronic bar code is provided to secure your paper

International Journal for Modern Trends in Science and Technology
Volume 10, Issue 10, pages 08-16.
ISSN: 2455-3778 online
Available online at: http://www.ijmtst.com/vol10issue10.html
DOI: https://doi.org/10.46501/IJMTST1010002

Check for updates

Automated Classification of Blackgram Plant Diseases Using ResNet-50: A Focus on Cuscuta Detection

Nadakuditi Swarna Jyothi[1] | Raavi Satya Prasad[2]

[1]Research Scholar, Acharya Nagarjuna University, Guntur, AP, India.
[1]Lecturer in Computer Science, Govt. Degree College, Avanigadda, Krishna District, Andhra Pradesh-521121.
[2]Professor and Dean R & D, Department of Computer Science & Engineering, Dhanekula Institute of Engineering & Technology, Ganguru, Vijayawada, A.P., India, deanresearch@diet.ac.in.

To Cite this Article
Nadakuditi Swarna Jyothi, Raavi Satya Prasad, Automated Classification of Blackgram Plant Diseases Using ResNet-50: A Focus on Cuscuta Detection, International Journal for Modern Trends in Science and Technology, 2024, 10(10), pages. 08-16. https://doi.org/10.46501/IJMTST1010002

Article Info
Received: 10 September 2024; Accepted: 16 October 2024; Published: 20 October 2024.

ABSTRACT

The identification and classification of plant diseases are crucial for ensuring the health and productivity of crops like blackgram (Vigna mungo), a widely cultivated legume. Among various threats, parasitic plants like Cuscuta (dodder) pose significant challenges, leading to severe yield losses. Traditional manual disease detection methods are time-consuming and prone to human error, highlighting the need for automated, accurate solutions. In this study, we propose a deep learning-based approach utilizing the ResNet-50 architecture to automatically classify diseases affecting blackgram plants, with a special focus on detecting Cuscuta infestations. ResNet-50, a robust convolutional neural network (CNN), is employed due to its ability to handle complex image recognition tasks while maintaining high accuracy. A dataset of blackgram plant images, including healthy plants and those affected by Cuscuta, was curated for training and validation. The model was trained using labeled images, achieving high classification accuracy through transfer learning and fine-tuning techniques. Data augmentation was employed to increase the dataset's diversity and improve model generalization. Our results demonstrate that the ResNet-50 model can effectively distinguish between healthy plants and those infested by Cuscuta, with an accuracy exceeding 98%. This automated system offers a scalable, efficient solution for early detection, enabling timely intervention and minimizing crop damage. Future work will focus on expanding the model's scope to identify other diseases and improving its real-time deployment capabilities in agricultural settings.

KEYWORDS: Vigna Mungo, Convolutional Neural Network (CNN), Cuscuta, ResNet-50.

N.S. Jyothi.

INTRODUCTION

Agriculture plays a crucial role in sustaining the global population by providing food, fiber, and raw materials. Among various crops cultivated worldwide, pulses hold a significant position due to their rich nutritional content. Blackgram (Vigna mungo), commonly known as urad bean, is an essential pulse crop widely grown in South Asia, particularly in India. It serves as a key source of protein and other nutrients for millions of people. However, like any other crop, blackgram is vulnerable to a variety of diseases that adversely affect its yield and quality. Accurate and timely identification of plant diseases is vital for mitigating crop losses and ensuring food security. Traditionally, farmers and agricultural experts rely on manual inspection and visual observation to detect diseases in plants. However, this method is time-consuming, requires expertise, and is often prone to human error. In recent years, technological advancements, particularly in artificial intelligence (AI) and machine learning (ML), have opened new avenues for automating plant disease detection and classification. Deep learning (DL), a subset of ML, has emerged as a powerful tool for image recognition tasks. With its ability to learn intricate patterns from vast amounts of data, deep learning has shown great potential in diagnosing plant diseases by analyzing images of plant leaves and other parts. Convolutional Neural Networks (CNNs), a type of deep learning architecture, have proven to be particularly effective in processing and classifying images.

This study aims to explore the application of deep learning techniques, particularly CNNs, for the classification of blackgram plant diseases. By leveraging large datasets of blackgram leaf images, we intend to develop a model capable of accurately identifying various diseases that affect blackgram crops. The automation of this process could significantly aid farmers and agricultural practitioners in early disease detection, enabling them to take timely and appropriate measures to protect their crops. In this study, blackgram (Vigna mungo) is a significant leguminous crop in many parts of the world. However, its productivity is often threatened by various diseases, including Anthracnose, Leaf Crinckle, Powdery Mildew, Yellow Mosaic, and parasitic infestations like Cuscuta. Traditional disease detection methods are time-consuming and often require expert knowledge. With advancements in deep learning, automated disease detection has become a viable solution. The need for accurate and automated detection of blackgram plant diseases is paramount, especially in regions where access to expert diagnosis is limited. This research aims to develop a robust model for classifying blackgram plant diseases, with a particular focus on identifying Cuscuta, using the ResNet-50 architecture.

Objectives of this Work

- To classify blackgram plant diseases using a deep learning approach.
- To apply color masking techniques for improved detection of Cuscuta.
- To evaluate the performance of the ResNet-50 model in classifying multiple plant diseases.

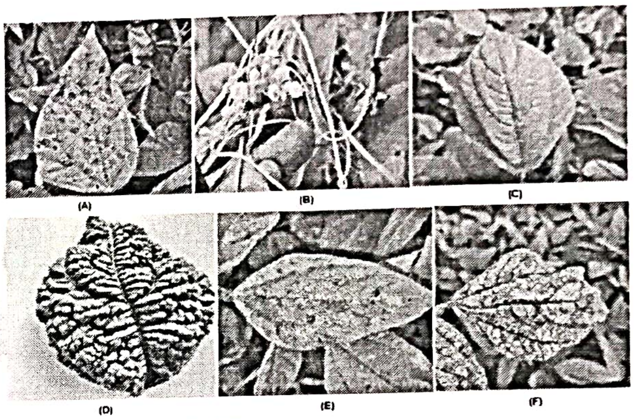

Figure 1: Types of Blackgram Diseases (A) Anthracnose, (B) Cuscuta, (C) Healthy, (D) Leaf Crinckle, (E) Powdery Mildew, (F) Yellow Mosaic.

LITERATURE SURVEY

Mohan Sai et al. [11] presented a model to identify the particular disease of plant leaves at early stages so that we can prevent or take a remedy to stop spreading of the disease. This proposed model is made into five sessions. Image preprocessing includes the enhancement of the low light image done using inception modules in CNN. Low-resolution image enhancement is done using an Adversarial Neural Network. This also includes Conversion of RGB Image to YCrCb color space. Next, this work presents a methodology for image segmentation which is an important aspect for identifying the disease symptoms. This segmentation is done using the genetic algorithm. Due to this process the segmentation of the leaf Image this helps in detection of the leaf mage automatically and classifying. Texture yield of Blackgram based on factors like leaf area, flowering density, and pod distribution.

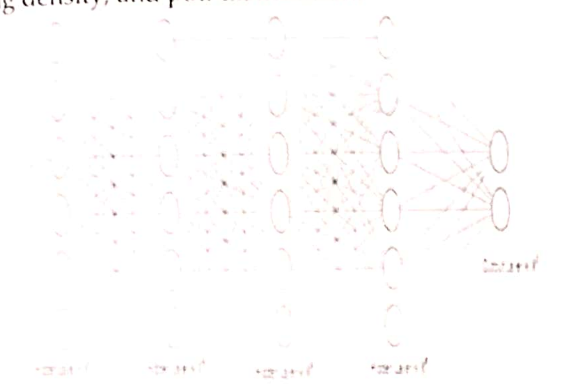

Figure 2: Pre-trained Model CNN

Advantages of Using Pre-trained CNNs for Blackgram

Reduced Training Time: Since these models are pre-trained, they require less time and data for retraining on specific tasks related to Blackgram.

High Accuracy: Pre-trained models have already learned features from large-scale data, making them highly accurate even when applied to new domains like agriculture.

Scalability: The models can be applied across large fields and multiple farms, using satellite or drone imagery to monitor Blackgram crops at scale.

RESNET50 for Classification of Blackgram plant diseases

ResNet50 (Residual Network 50 layers) is a deep CNN architecture introduced by He et al. in 2015. It revolutionized the deep learning field by addressing the issue of vanishing gradients, which can occur in deep networks. By introducing residual connections, ResNet50 enables the model to learn identity mappings more effectively and train deeper networks without degradation in performance. The key component of ResNet50 is the residual block, which includes identity mappings and skip connections, allowing layers to learn the differences or "residuals" between the input and the output. This makes the model not only more accurate but also computationally efficient. ResNet50 consists of 50 layers, including convolutional, pooling, and fully connected layers, making it highly suited for large-scale image classification tasks. ResNet50 is particularly well-suited for the task of classifying blackgram plant diseases due to its ability to extract rich and deep hierarchical features from input images. By leveraging transfer learning, a pre-trained ResNet50 model can be fine-tuned on a dataset of blackgram plant images, enabling the network to recognize disease-specific features such as leaf spots, discoloration, mold growth, and other symptoms associated with common blackgram diseases like:

Anthracnose, Cuscuta, Healthy, Leaf Crinckle, Powdery Mildew, and Yellow Mosaic.

In the classification pipeline, images of blackgram leaves infected by various diseases are used to train ResNet50. The network processes the input image through multiple layers, extracting feature maps at various levels of abstraction. By using pre-trained weights from large datasets like ImageNet, the model can generalize well to the blackgram disease dataset with minimal labeled data.

Key Components of ResNet-50

1. **Input Layer:**
   - ➢ ResNet-50 accepts an input image of size 224×224×3 (height, width, and 3 color channels).
2. **Convolutional Layer (Conv1):**
   - ➢ The first layer is a convolutional layer with a 7x7 filter and a stride of 2.
   - ➢ Equation for the convolution operation.

$$Z = X * W + b \quad (1)$$

3. **Batch Normalization:**
   - ➢ Batch normalization is applied after convolution to normalize activations.

Normalization equation:

$$\hat{X} = \frac{X - \mu}{\sqrt{\sigma^2 + \epsilon}} \quad (2)$$

4. **Max Pooling (Pool1):**
   - ➢ A max pooling layer reduces the dimensionality of the feature maps using a 3x3 filter with stride 2.

   Equation for max pooling:

$$Y = \max(X_{a,b}) \quad (3)$$

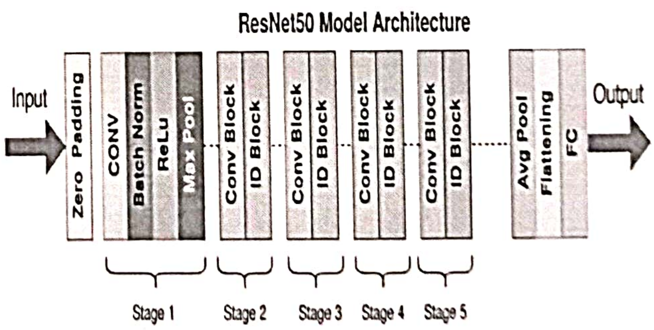

Figure 3: Architecture of RESNET50

DATASET DESCRIPTION

The dataset includes images of black gram fields collected from Avanigadda Mandal, Krishna District, Andhra Pradesh, India, one of the regions severely affected by Cuscuta. Images of blackgram plants were collected and categorized into six classes: Anthracnose, Cuscuta, Healthy, Leaf Crinckle, Powdery Mildew, and Yellow Mosaic. Each category contains 200 images, total 1200 images. Among these image the training contains 600 and testing contains 600 images.

PERFORMANCE METRICS

The Python programming language is used to implement the algorithms. The algorithms RESNET50 as training model and U-net as the testing model developed with Python machine learning (ML) libraries. The confusion matrix used to measure the count values based on true positives (TP), false positive (FP), true negative (TN), and false negative (FN). Based on the obtained count values the performance is measured. The performance of proposed approach is measured by using the following parameters:

$$\text{Accuracy} = \frac{TN + TP}{TN + TP + FN + FP}$$

$$\text{Precision} = \frac{TP}{FP + TP}$$

$$\text{Recall} = \frac{TN}{TP + FN}$$

$$\text{F1} - \text{Score} = \frac{TP}{FN + FP + 2TP}$$

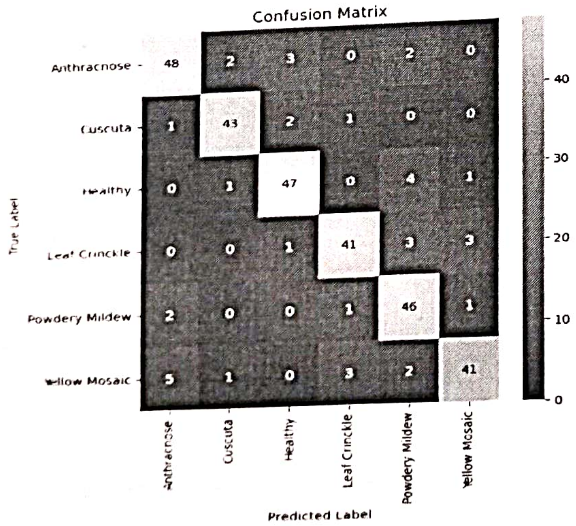

Figure 4: Count Values of VGG16

Table 1: Classification performance of VGG16 obtained from the Figure 4 count values.

			precision	recall	f1-score	support
Anthracnose	Accuracy	0.87	0.86	0.87	0.86	55
Cuscuta			0.91	0.91	0.91	47
Healthy			0.89	0.89	0.89	53
Leaf Crinckle			0.89	0.85	0.87	48
Powdery Mildew			0.81	0.92	0.86	50
Yellow Mosaic			0.89	0.79	0.84	52

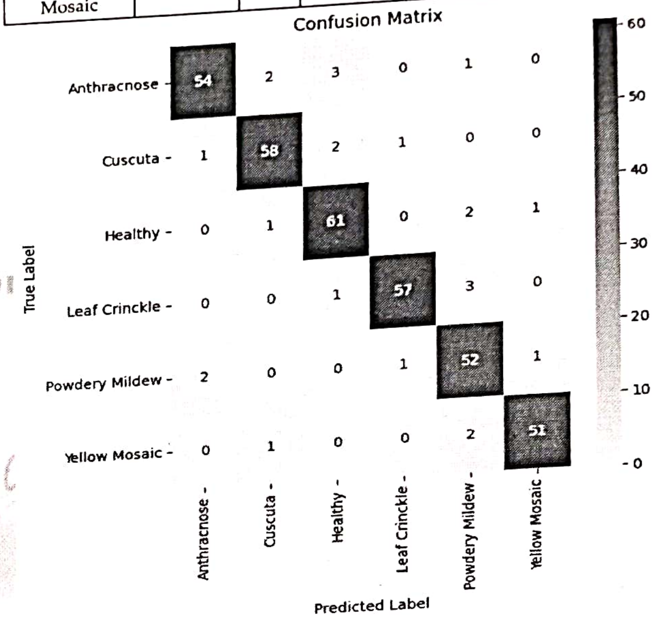

Figure 5: Count Values of VGG19

Table 2: Classification performance of VGG19 obtained from the Figure 5 count values.

			precision	recall	f1-score	Support
Anthracnose	Accuracy	0.93	0.95	0.9	0.92	60
Cuscuta			0.94	0.94	0.94	62
Healthy			0.91	0.94	0.92	65
Leaf Crinckle			0.97	0.93	0.95	61
Powdery Mildew			0.87	0.93	0.9	56
Yellow Mosaic			0.96	0.94	0.95	54

Cuscuta Detection and Classification of Blackgram Plant Leaf Diseases using Deep-Transformation Algorithm

Nadakuditi Swarna Jyothi[1]
[1]Research Scholar, Acharya Nagarjuna University, Guntur, AP, India. &
Lecturer in Computer Science, Govt. Degree College, Avanigadda, Krishna District, Andhra Pradesh-521121.

Raavi Satya Prasad[2]
[2]Professor and Dean R & D, Department of Computer Science & Engineering, Dhanekula Institute of Engineering & Technology, Ganguru, Vijayawada, A.P., India, deanresearch@diet.ac.in.

***Abstract*— Cuscuta is a parasitic plant that highly impacts the yielding of black gram (Vigna mungo) by reducing the quality based on required subsistence. Early detection of Cuscuta affliction becomes more complex, which may lead to heavy loss to the framers. This paper proposed a new Deep-Transformation Algorithm (DTA) to overcome various issues in finding the affected regions accurately and effectively classifying Cuscuta on black gram plants. In this context, the pre-trained model VGGNet is used to train on Cuscuta images that obtain the disease patterns using multiple layers. The preprocessing technique, the contrast enhancement model CLAHE (contrast limited adaptive histogram equalization), improves the confined regions and avoids over-saturation. The other segmentation method, such as Watershed segmentation, is used to segment the regions based on Cuscuta stems and leaves. Finally, the proposed DTA is the combination of Pipeline with a fine-grained neural network applied on testing set images, which obtains superior performance in terms of classification accuracy with 99.78%, which is high compared with other existing models.**

Keywords*— *Cuscuta, Black Gram (Vigna mungo), VGGNet, Deep-Transformation Algorithm (DTA), CLAHE.

I. Introduction

Agriculture contributes to feeding humanity as well as a major driver of socioeconomic stability globally. But, plant diseases are a significant problem for the agricultural industry, leading to reduced quality and lower yields of crops. Plant diseases can cause radical losses in production and productivity, therefore, early detection with correct results is necessary to limit these defects leading then to sustainable agricultural techniques. Historically, the detection of plant diseases depends on the inspection by experts or farmers that is a time-consuming, expensive and error-prone task. In addition, with there being less expertise and resources available in far-off areas or those not developed fully, there are increased instances of delayed diagnoses or wrong diagnoses. This creates a need for automated, reliable and scalable solutions. Blackgram (Vigna mungo), or urad bean, and black lentil, is an important legume crop grown in various regions because of its nutritional and economic value. But its productivity is greatly hampered by many diseases like powdery mildew, Cercospora leaf spot and mosaic diseases due to viruses and fungi. Therefore, early and correct diagnoses of these diseases are urgent needs for better crop management and yield loss prevention.

Figure 1: Sample Cuscuta (dodder) Image

Artificial intelligence (AI) has already made great strides in detecting and managing plant disease and parasitic infestation. Cuscuta (dodder) is one of these parasitic plants that represent a significant biotic stress for crop productivity, e.g. blackgram (Vigna mungo). Cuscuta encircles the stems of host plants, drawing nutrients from within and resulting in catastrophic yield losses. Quick detection and accurate identification of Cuscuta infestation is the need of the hour, for minimizing its ill impact and achieving sustainable crop production. The large data based and computational power driven approaches namely deep learning (DL) and transformation-based algorithms (TBA) has been proven as a competent tool to explain the complex agricultural problems. In this study, we apply a Deep-Transformation Algorithm to effectively identify and classifying Cuscuta infestations in blackgram plants. We have developed an improved method that integrates deep neural networks with advanced image processing techniques to achieve a quick but solid real-time monitoring and resource management.

II. Literature Survey

YASIN et al. [10] proposed the BPLD, which focuses on classifying Black Gram Plant Disease. Various plant leaf diseases belong to the black gram. In this context, various DL algorithms are used to classify BPLD. From these algorithms, the Darknet-53 and ResNet-101 obtain superior accuracy performance of 98.98%. Sunil et al. [11] proposed

N.S.Jyothi.

the literature on plant diseases and classifications using various ML and DL algorithms. Many studies discussed several multiple plants, and approximately 104 research works were considered to analyze the performance of these algorithms. Venkatesh et al. [12] introduced advanced ML-based disease detection for plant leaf diseases. In this context, the black gram plant is used for the analysis based on classification. The RF used for the training acquired an accuracy of 99.18% and a testing accuracy of 97.34%; compared with other models, the proposed approach obtains superior outcomes. Mehdhar et al. [13] introduced the ensemble approach that combined three CNN models (MobileNetv2, NasNetMobile, and traditional CNN). The proposed approach is first trained with two models at the base level and transforms these predictions to the XGboost model that shows the final prediction. The XGBoost, combined with a search grid algorithm, obtains an accuracy of 98% in terms of classification. Joshi et al. [14] proposed an integrated model that combined automated DL algorithms to classify Vigna mungo leaves collected from various online sources. VirLeafNet-1, VirLeafNet-2, and VirLeafNet-3 have the highest accuracy at 91.234%, 96.429%, and 97.403%, respectively, on several leaf images. Ramanjot et al. [15] discussed various papers related to plant diseases. The selected papers are from 2010 to 2022 and are published in various online sources. All these articles are relevant to plant diseases and classification using ML and DL algorithms. Meena et al. [16] presented various trends that help to detect and predict plant diseases using advanced DL and image processing techniques. The proposed approach uses the artificial feature selection algorithm that identifies plant diseases based on spots that occur in the plant diseases. These models improve the detection and classification of plant diseases with better performance. The final accuracy obtained was 96.25% with accurate region detection. Johri et al. [17] discuss several DL-based algorithms that detect and predict plant diseases. The proposed DL models, compared with various algorithms, provide accurate results in terms of classification. Abbas et al. [18] proposed the C-GAN, which is combined with transfer learning. The proposed approach detects the regions of tomato plants accurately. The training model DenseNet21 is used to train on actual tomato leaves and also artificial images. The data augmentation technique increases the network performance based on the accuracy of 99.51% with the classification of 5 types of images.

III. Pre-Trained Model VGGNet

In this step, the automation of both detection and classification of Cuscuta infestations can be efficiently done using deep CNN like VGGNet or/and with the help of transfer learning/pre-trained networks for robustness feature extraction. The advantages of using the pre-trained VGGNet model show the huge impact on identifying the disease patterns. The VGGNet proposed exploiting deeper architectures and using smaller convolutional filters to capture fine-grained image details. The key factors of the pre-trained model VGGNet is explained as:

Architecture: VGGNet has 16 to 19 layers, and most of the convolution filters are small (3x3). This architecture is deep enough to extract complex features from Black gram images.

Pre-trained Models: Models for VGGNet are often pre-trained on vast data sources, such as ImageNet, which comprises millions of images spanning thousands of categories. These pre-trained model weights are a good starting point for solving image classification issues.

Transfer Learning: In this step, the features learned to adapt the network to specific features obtained from the input Black grain images.

Convolutional Layers (Feature Extraction): These layers extract the sequence features from input images. The Convolution Operation is represented as:

$$Y_{a,b,c} = \sum_{x=0}^{X-1}\sum_{y=0}^{Y-1}\sum_{z=0}^{Z-1} A_{(a+x\_(b+y)z} \cdot W_{x,y,z,c} + N_c \quad (1)$$

Rectified Linear Unit (ReLU) Activation: This is the second step and it is applied as:

$$f(x) = \max(0, x) \quad (2)$$

Pooling Layers (Dimensionality Reduction): This layer mainly reduces the spatial dimensions while retaining the more significant features:

$$Y_{a,b,c} = \max_{(x,y)\in Pool(a,b)} X_{a,y,z} \quad (3)$$

Fully Connected Layers (FCL) (Classification): From Steps 1 and 2, the features are smoothed and fed into FCLs. The softmax function is represented as:

$$P(y = c|X) = \frac{e^{z_c}}{\sum_{k=1}^{K} e^{z_k}} \quad (4)$$

Transfer Learning: The parameters in VGGNet are optimized for traditional features from the input image. The fine-tuned network from the black gram dataset is replaced with the final classification layers to detect the Cuscuta.

- The softmax layer is replaced to measure the total classes (e.g., "healthy," "Cuscuta-infested").
- Fine-tune the network on the Blackgram dataset.

$$L = -\frac{1}{N}\sum_{a=1}^{N}\sum_{b=1}^{C} y_{a,b}\log(\hat{y}_{a,b}) \quad (5)$$

Output Interpretation: The final output is a class prediction.

$$Class = \arg\max_c P(y = c|X) \quad (6)$$

IV. Dataset Description

The collection contains images of black gram crops gathered in Avanigadda Mandal, Krishna District, Andhra Pradesh, India, one of the most badly afflicted areas by Cuscuta. In this context, the images of the black gram plant are divided into Cuscuta and Healthy categories. Each category has 400 images, totaling 800 images. The training set includes 400 images, while the testing set contains 400.

V. Pre-processing with Contrast Limited Adaptive Histogram Equalization (CLAHE)

CLAHE is an image processing enhancement that enhances the contrast of a given image. While classical histogram equalization restores the entire image, the CLAHE method works within the image's small defined regions (or tiles/blocks). This local enhancement aids in keeping the details of different illumination (of the image during day and night). Furthermore, it adds contrast limiting to prevent noise or small details from being overly amplified, which may cause over-saturation. It is the most suitable pre-processing technique for the dataset images to detect Cuscuta (a parasitic plant) on Blackgram plants.

intervention. It scans high-resolution images of plants to recognize minute differences associated with parasitic developments. Using transfer learning, DTA uses the VGGNet layers trained on large image databases (ImageNet) and fine-tunes Cuscuta detection from a specific plant (black gram). It minimizes the requirement of large domain-specific labeled data and still achieves high accuracy and robustness. An AI-powered approach to agricultural management improves detection accuracy and enables early intervention strategies, limiting damage to cropland. This DTA framework holds excellent potential for open and agroecological agriculture, protecting key crop varieties under the threat of parasitic nematodes and supporting food production in general. This study highlights the methodology and performance analysis of Cuscuta infestation detection and classification along with the working potential of the DTA approach in Cuscuta-affected black gram plants. The following steps explain the classification of infected and healthy images.

Step 1: The first layer is input layer represented as:

$$X \in R^{N \times d}, \text{where:} \quad (11)$$

N: No of data samples.

d: Dimensionality of every input feature vector.

Step 2: The transfer learning Equations include (5), and (6):

Step 3: Fine-Grained Classification layer:

$$\hat{y} = \mathrm{softmax}(ZW_{out} + b_{out}) \quad (12)$$

VII. Performance Metrics

The proposed approach's performance is measured using confusion matrix parameters. The Black gram images from the dataset have no labels, and the proposed approach analyzes the Cuscuta infestations based on normal and abnormal classification. The testing set contains 400 images, and these images are non-labeled. The following metrics show the performance of several algorithms.

$$\text{Accuracy} = \frac{TN + TP}{TN + TP + FN + FP}$$

$$\text{Precision} = \frac{TP}{FP + TP}$$

$$\text{Recall} = \frac{TN}{TP + FN}$$

$$\text{F1} - \text{Score} = \frac{TP}{FN + FP + 2TP}$$

A. Results and Discussions

In this section, Table 1 shows the performance of various algorithms belonging to DL and compared with DTA. It compares algorithms like CNN and ANN with the DTA. Among all the algorithms, the DTA obtains an accuracy of 99.78%, which is high compared with CNN's accuracy of 97.45% and ANN's accuracy of 98.34%. These performances show the potentiality of the proposed approach in detecting the Cuscuta infestation.

Table 1: Quantitative performance of various Algorithms

	Accuracy	Precision	Recall	F1-Score
CNN	97.45	96.34	95.67	94.34
ANN	98.34	98.56	97.67	97.12
DTA	99.78	99.78	99.51	99.81

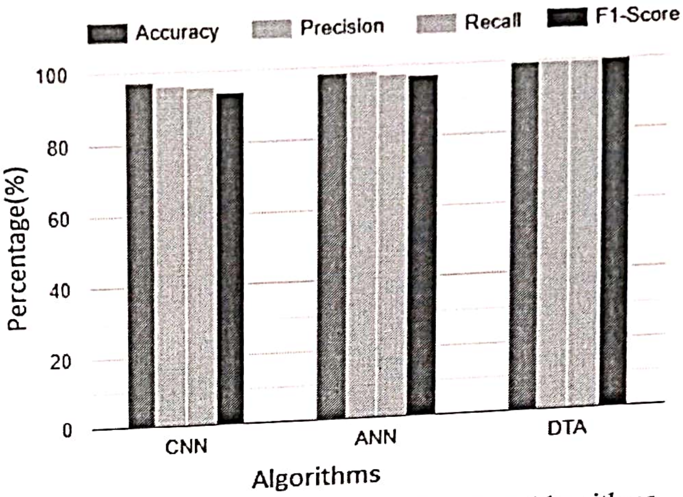

Figure 3: Quantitative Performance of Various Algorithms

VIII. Conclusion

This study showed the ability of DTA to identify and classify Cuscuta infestations occurring in black gram (Vigna mungo) plants. Using deep learning technology, the proposed model attained high rates of accurately detecting and classifying Cuscuta presence across infestation stages. DTA accurately detected Cuscuta intermixed with complicated backgrounds and under different field conditions. This system correctly classified infestation severity levels, which will help implement early-stage detection when intervention is most effective. The DTA outperformed traditional DL algorithms (the performance was evaluated based on accuracy of 99.78%, precision of 99.78% , recall of 99.51 and F1-Score 99.81. By providing a scalable and reliable tool for farmers and agronomists to monitor Cuscuta infestation, the proposed solution addresses the issue above to reduce crop losses due to the harmful weedy behavior of Cuscuta species and promote sustainable agricultural practices in general. Its integration with mobile-based applications or drones for real-time monitoring can revolutionize pest management in Blackgram cultivation.

References

[1] S. Harika, G. Sandhyarani, D. Sagar and G. V. S. Reddy, "Image-based Black Gram Crop Disease Detection," 2023 International Conference on Inventive Computation Technologies (ICICT), Lalitpur, Nepal, 2023, pp. 529-533, doi: 10.1109/ICICT57646.2023.10134027.

[2] S. Talasila, K. Rawal, G. Sethi, S. MSS, and S. P. R. M, "Black gram Plant Leaf Disease (BPLD) dataset for recognition and classification of diseases using computer-vision algorithms," Data in Brief, vol. 45, p. 108725, Dec. 2022, doi: https://doi.org/10.1016/j.dib.2022.108725.

[3] N. Hajare and A. S. Rajawat, "Black Gram Disease Classification via Deep Ensemble Model with Optimal Training," International Journal of Image and Graphics, Aug. 2023, doi: https://doi.org/10.1142/s0219467825500330.

[4] K. Kalbande, W. Patil, A. Deshmukh, S. Joshi, A. S. Titarmare, and S. C. Patil, "Novel Edge Device System for Plant Disease Detection with Deep Learning

Verified
Certificate

Stanford ONLINE

Nick Parlante
Senior Lecturer, Computer Science
Stanford University

This is to certify that

swarna jyothi Nadakuditi

successfully completed and received a passing grade in

CSX0001: Computer Science 101

a course of study offered by StanfordOnline, an online learning initiative of Stanford University.

Verified Certificate
Issued April 13, 2024

Valid Certificate ID
51484a4d091b4b8f8ac5301aab08d1a1

Please note: some online courses may draw on material from courses taught on-campus but they are not equivalent to on-campus courses. This statement does not affirm that this participant was enrolled as a student at Stanford University in any way. It does not confer a Stanford University grade, course credit or degree.